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Simulating Active Perception and Mental Imagery with Embodied Chaotic Itinerancy

Abstract: *We explore the understanding of conscious states in terms of spatio-temporal dynamics through modelling a mobile agent. Conscious states are associated with an agent's spontaneous and deterministic fluctuation between attachment to and detachment from the surroundings. It is because of this fluctuating nature, we argue, that an agent can perceive structure in the world. Perception requires a conscious state in physical devices. This is a central concern of this paper, and we examine it by simulating a mobile agent equipped with an interconnected Fitz-Hugh-Nagumo (FHN) neuron network with delayed signal transmissions. The agent can move around a space by sensing the environment pattern through the input neurons and computing the motor outputs via the FHN network.*

The agent shows a variety of motion styles and a spontaneous selection of motion styles responding to the surroundings. Such a phenomenon is named embodied chaotic itinerancy (ECI), as an extension of chaotic itinerant dynamics, which is known to be a typical dynamic with a high degree of freedom. We take this selective mode of response to be significant, particularly those interacting with spatial pattern, as an inevitable property of conscious states.

1. Introduction

This paper demonstrates the importance of random-seeming exploration behind the regular and coherent cognitive processes which

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underlie conscious perception. We pick up meaning as we touch objects but our touching behaviour doesn't have a coherent motion; rather it looks like a random explorative process. We pick up meanings as we look at objects, but the visual process is supported by a 'random' saccade motion. This randomness, underlying human and animal perception, is what we notice as the main difference between human and machine sensory systems. Why do we need randomness? How is it related to consciousness? Below I will argue what we really see is not randomness but embodied chaos. From this I propose embodied chaotic itinerancy as a novel concept for understanding consciousness and illustrate this with a simulation study of active perception.

Consciousness concerns self-organized, temporal structures in a coupling between the brain and the environment. Edelman (2003) attributed the brain-environment coupling to the reentrant activity of an integrated circuit in a brain system. From a dynamical-systems studies point of view, analysis of the kinds of attractors and/or information flows in a phase space have been used to understand the dynamic nature of neural activities (see, e.g., Tsuda 2001; Freeman 2003a, b) In particular, chaos and chaotic itinerancy (CI) appeared as salient properties of a brain system.

Chaotic Itinerancy is a relatively common feature among high-dimensional chaotic systems, which shows itinerant behaviour among low-dimensional local attractors through higher-dimensional chaos (Ikeda *et al*., 1989; Kaneko & Tsuda, 2003). Briefly speaking, CI is an itinerant behaviour among chaotic attractors (but they are not attractors in the strict sense as a system can't stay there indefinitely). An entire system demonstrates chaotic behaviour but eventually changes its effective degrees of freedom and the associated spatio-temporal patterns. The notion of CI in a brain has been intensively studied by Tsuda (2001) with respect to episodic memory and has also been studied experimentally and theoretically by Skarda and Freeman (1987) with respect to the olfactory bulb in rabbits. So far, CI has only been defined properly in a closed system with no feedback from the environment. A proper mechanism for, and mathematical definitions of CI have not yet been revealed. Several different mechanisms for CI have been proposed, for example, CI is caused by individual chaotic elements or by the network topology of the elements. It has also been discussed whether CI is caused by, or is similar to, the dynamics of the Milnor attractor (Kaneko, 2002).

However, although CI has only been studied properly in a closed systems it is ubiquitous in high-dimensional systems. Also, since CI

can be observed irrespective of conscious states or living states, we can't simply say that CI is sufficient for describing life or conscious states. We must develop a new logic/dynamics additional to the idea of CI, in particular with respect to embodiment. A recent idea has been to introduce natural constraints that ground CI in a robot's navigation behaviours (Tani, 1998), where a spontaneous breakdown of stable navigation dynamics is taken as a sign of minimal self-consciousness. Having an open, spatial environment, an agent is faced with a hierarchy of different time scales; navigation time scales, local-attractor time scales, and transition time scales which collectively organize a coherent agency. These time scales are not independent but are generated in a way that is mediated by a neural dynamics such as that presented in this paper. We are interested in this type of CI in a spatial environment and in navigation roles, as it provides an example of CI in an open system. We call this *embodied chaotic itinerancy* (ECI) below.

The dynamical perceptual states that arise from self-motion behaviour are investigated with a model based on ECI. Take an example from tactile experience. When we touch an object, we tend to think that the information is coming from the texture of the object but what we feel isn't an inherent property of the object — but is rather the information generated from our own motion pattern. When we move our hands, the momentary feeling is retained in the motion space that drives the successive action pattern. Consecutive sense flow associated with the action pattern organizes the information structure of the object (e.g. perception of a *peau de soie* requires your hand movement, but that movement isn't part of the object).

The action pattern can synthesize a time structure that is meaningful only to the subject but the movement looks merely random from a third person's point of view. Such distinctions between the randomness from the third person's point of view and the meaningfulness from the first person's point of view is, I believe, what consciousness is all about. It is reflected in the way action is generated, where the difference between sense-making and randomness should be scrutinized. Namely, perception isn't a simple interplay between sensation and self-motion, but involves more complex processing such as exploration and a bundling of action patterns. An ordinary action pattern contains an unseen set of action sequences, which results in slipping behaviours (Reed, 1992). For example, hesitation or a trajectory change is detected when one reaches for, or grasps, objects. Such slipping phenomena are not error phenomena, but evidence of action autonomy rather than intentional action control. Each local action unit

has its own local goal. Gibsonian psychology (Reed, 1996) refers to this characteristic of perception as 'active perception'. This perspective insists that exploration processes organize our sensory experience, stressing that the process of exploration itself is more important than its attainment of the final action plan. Affordances of objects trigger a corresponding style of motion of a subject that interacts with the object. Gibson (1962) argues that visual perception of an object has the goal of exploring the affordances of the object. This is where the meaning of the object comes from as referred to in the first paragraph of this section.

We argue that styles of motion can account for the meaning of objects (Iizuka and Ikegami, 2003; 2004; Ikegami and Zlatev, 2006). Our contention is that ECI is good at describing this nature of active perception and explaining an important dimension of conscious states, i.e. self-simulation and attachment/detachment processing, because we think that a conscious state is defined where an agent's autonomous internal world is assured independently from the open spatial environment. Autonomy of agents becomes clear when agents can simulate themselves and adjust their couplings with the environments.

In the succeeding sections, we illustrate these ideas with reference to a mobile agent model equipped with a network of unstable elements. This agent can change its navigation styles because of the unstable properties of its constituent neurons. After investigating the spatio-temporal dynamics of this system, we discuss their significance for studying conscious states.

2. Modeling with an FHN Network

We study the exploratory behaviours of a mobile agent that is endowed with a network of the Fitzhugh-Nagumo neurons (Fitzhugh 1961, Nagumo 1962). The Fitzhugh-Nagumo (FHN) model is a simplification of the Hodgkin-Huxley model that describes, for the first time, the depolarization of a neural membrane. Each FHN neuron consists of two variables: a 'fast' variable (u) responsible for the excitation of a membrane potential and the 'slow' variable (v) responsible for its non-responding dynamics. An input signal is given to the fast variable u. The system has been studied intensively as to its bifurcation structure and attractor properties (see, e.g. the review by Kostova *et al.*, 2004). It is known that the membrane's spiking behaviour is well controlled by the periodicity of the input pulse trains. In particular, chaotic behaviour was found in the sub-threshold dynamics

(Kaplan 1996). Here we study a network of the FHN neurons with the time delayed connections. We assume that when a neuron (fast variable) is activated ($u > 0$), a pulse signal is transmitted to the connected neurons with a time delay. A recipient neuron will receive a pulse signal of a certain width and height after an assigned time lag from the sender neuron. This time lag is unique to this neural system. For simplicity, we assume just two different values of time lag.

We now discuss an agent that can sense an environmental signal and can move around by itself. An information flow from the sensor input to the motor output is computed and mediated by the described coupled FHN neurons. This agent is assumed to have a circular body and the FHN neuron sensors are attached on the body surface. We classify the neurons into 3 groups: input, internal and output. Input neurons can directly access the external signals and respond to them by sending/suppressing signals to internal neurons.

FHN neurons are randomly and sparsely connected (e.g. the connecting probability between two neurons is set at 20%) with each other. In the current example, we use 10 input, 16 internal and 4 output neurons. The input neurons are arranged along the circumference of the agent's body of radius 10 at an equal distance apart. An environment is a two-dimensional pixel array with a graded amplitude of stimulus. The agent receives signals from the pixel bit below each input neuron. If an agent stays in the same position, the input neuron constantly receives the same input value from the pixel beneath the body.

Signals from the input neurons are mediated by the internal neurons and are transferred to the output neurons again with a given time delay. The output neurons cooperatively constitute the motor actions. The explicit forms of the FHN neuron equations and the force vectors that are used, are given in the Appendix.

In order to focus on the issue of time structure, we discarded some important aspects of generic neural network systems. First, no excitatory or inhibitory signals are assumed. Due to the basic characteristics of the FHN neuron, pulse train inputs can activate a recipient neuron but also suppress it, depending on the width, height and periodicity of the input. Therefore, no explicit plus or minus sign was assigned to the connections. Second, we don't integrate the signal amplitudes at the recipient neuron. Therefore, exactly coincident signals are equivalent to a single pulse. However, a slight difference in signalling timing will cause the irregular pulse trains. For example, successive signals are concatenated to produce a large pulse width. This happens to vary the activation mode of the recipient neuron state.

Because of the finite pulse width, an exact coincidental pulse gives short-lived forces as such input pulses are regarded as a single pulse. Also, pulses with different phases generate longer-lived inputs, which sometimes generate weak but long-lived forces. This feature enables a variety of motion styles. Using these forces, we can simulate agents' various rotating motions, which is a combination of moving forward and rotating (the exact forms of equation are provided in the Appendix).

3. Basic Characteristics

A real neuron has a threshold for firing and a non-responding time period. A formal neuron is modeled with these as its basic parameters. For the FHN neuron, however, the threshold and non-responding time appear to be natural outcomes of the dynamical system's properties.

A typical responding function of the FHN neuron is depicted in Fig. 1. By receiving a single pulse with a sufficient strength and width, the FHN neuron can overshoot. When the input signal is given as a train of pulses, the responding behaviour becomes rather complicated. The width of the output signal, which is defined as an onset of overshooting, is computed as the width of the input signal. Locally it becomes proportional to the input width but then the tendency breaks down and chaotic response emerges. The complex nature of the FHN system is essential for the CI behaviour in what follows. In below every time step is numbered with the Runge-Kutta update steps.
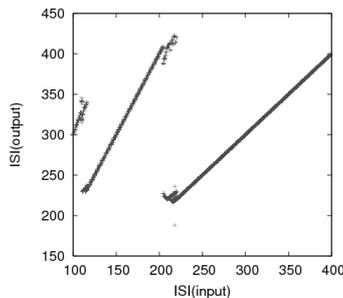

Figure 1. Response of a single FHN neuron against periodic pulse train. The inter-spike intervals (ISI) in output signal of the single FHN neuron (y-axis) is plotted in one picture after eliminating transients. Changing the ISI of the input pulse train (x-axis), the output ISI also varies and sometimes it changes from periodic (where you have only a single point) to chaotic (where you have multiple points). The parameter sets are, I=0.7, a=0.7, b=0.8 and C=10 (see the Appendix for explanations of the significance of the parameters). The ISI is named 'width' of the signal in the main text.

4. Observations

We present an example of the agent's exploration behaviours in a two-dimensional plane. The example has a checkerboard with two different textures. When an agent moves across the edges, pulse trains are generated as for the input neurons. For example, in this experiment, the higher value of the rectangular time series is set at 0.28 and the lower one is at 0.21 When an input neural state overshoots (i.e. the fast variable becomes greater than zero), it will send a rectangular pulse of that property to its recipient neurons. For the inter-neural signals, we typically use 0.7 for the highest value of the pulse and 0.0 for the lowest. The width of the pulse is around 20. Depending on those parameters of the pulse train, we have a variety of motion styles.

First, we show typical chaotic itinerant behaviour by depicting its averaged neural activities (Fig. 2) and the associated spatial navigation trails (Fig. 3). Fig. 2 demonstrates a spontaneous switching of different neural activity modes. In Fig. 2, the upper line expresses the input neural activities and the lower one expresses the internal neural activities. Exploratory behaviour with a certain style of motion produces the effective pulse trains, which cause the input neurons to fire and alternate the successive exploratory behaviour. Such exploratory styles of motion and the spontaneous mode switching are clearly observed in Fig. 3. In this figure, successive styles of motion are provided by overwriting spatial trails in each 10000 time steps. Internal neural states can have a variety of local and global attractors, so that it can sustain a clear style corresponding to each type of attractor. As a result of interference between the internal and input neurons, an agent autonomously selects the style of exploratory behaviour.
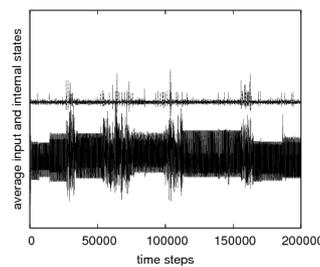
Figure 2 (see colour plate at back). Itinerant behaviour of the integrated input and internal neural activities. Different temporal patterns correspond to the different local attractors. This is associated with the spatial patterns in Fig. 3. The upper line corresponds to the input neural activities and the lower one to the internal activities. The set of parameters used are a=0.7, b=0.8 and c=10.
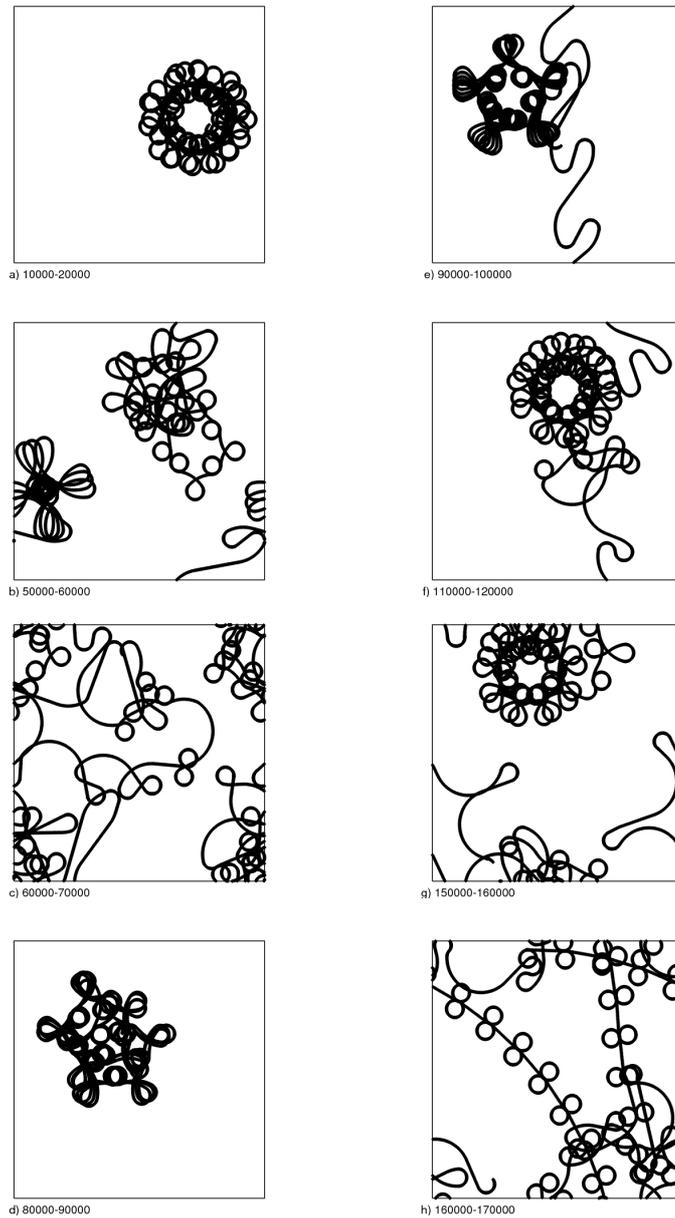
Figure 3. Time evolution of navigation patterns. A structure of motion pattern wanders among local attractors. From the left upper corner (a) to the right bottom corner (h), spatial trails are overlaid for each 10000 time steps.
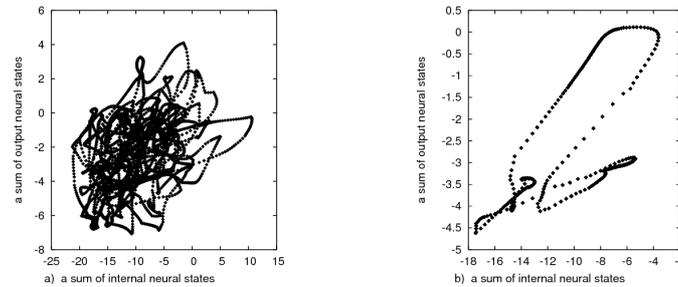
Figure 4. Examples of return maps from the local periodic and chaotic attractors in Fig. 3. The integrated output neuronal activities are plotted against the average internal neural activities by truncating the external inputs . A smooth limit cycle corresponds to the periodic (b) attractors corresponding to Fig.3 (a) and the noisy ones to the local chaotic transients (a) corresponding to Fig.3 (c).

When an internal neural state collapses to a periodic attractor, its motor output becomes periodic so that the navigation trail also becomes periodic. If no new inputs are given from the environment, the agent's periodic motion is eventually preserved. However, if the state is chaotic, the periodic motion often becomes unstable and a new motion structure appears without having external inputs. In Fig. 2 and Fig. 3, time steps of around 30000, 60000, 105000 and 160000 are local chaotic transients (which eventually go to a periodic states after about 10000 time steps).

A general situation is in between the two cases. Input neurons don't fire against excess pulse trains. They only fire when the pulse trains have some accents. Namely, the input trains should have a contrast between quiet and busy phases. A continual spiking time-series can't let neurons fire. Those input patterns are indirectly controlled by the agent's navigation pattern. Therefore, some navigation patterns generate input signals that can cause the input neurons to fire, which leads to changed navigation patterns.

In this way, chaotic itinerant behaviour is generated by the sensory-motor coupling.

As described above, it sometimes happens that some navigation styles with given spatial patterns can't activate input neurons. Yet, the navigation style changes from time to time. This is essentially caused by the chaotic itinerant dynamics within the internal network.

Chaotic and periodic local attractors can be distinguished by drawing the return map of the internal neural dynamics by truncating the

external inputs manually. Here I draw a 2-dimensional return map of the internal and output neurons in Fig. 4 and 5. A clear limit cycle is obtained for the local periodic attractor and a scattered pattern is observed in the chaotic (transient) one. A true chaotic case of no external input is given with its navigation pattern. In this chaotic case, clear style of motion is often hard to detect because of the chaotic nature.

By changing the spatial scales of the checkerboard pattern which we used as a spatial environment for this simulation, we noticed that only a certain spatial pattern caused CI navigation motion. This is well understood since the spatial scale determines the temporal interval of successive stimuli and the navigation style is highly sensitive to the input organization. In a certain range of space-time scales, an agent

a) 50000-60000

c) 190000-200000

b) 90000-100000

d) a sum of internal neural states
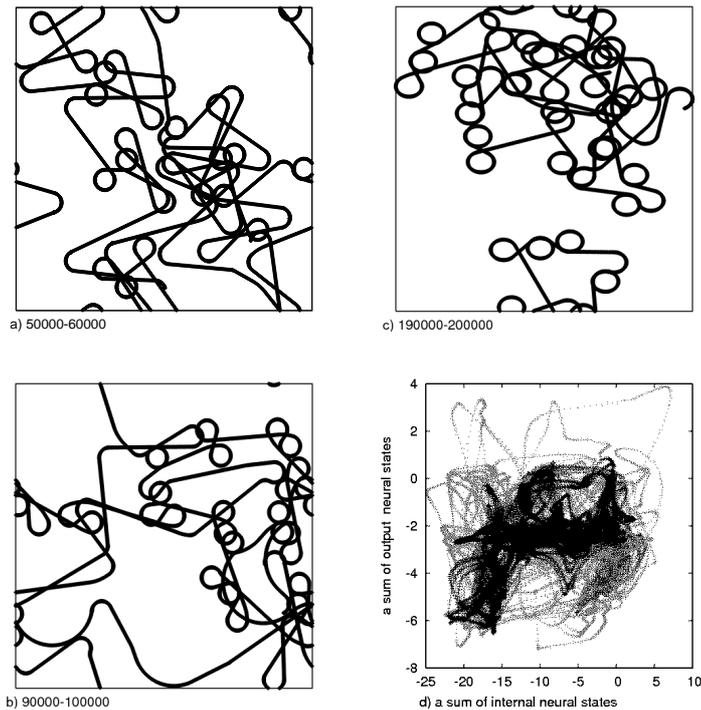
Figure 5. Here we show return maps for the cases without external inputs, which change spontaneously from the states indicated from red to green to blue (d — see colour plate at back). The corresponding navigation trail to each return map is depicted in (a–c).

shows chaotic itinerancy of navigation styles. We summarize the implications from the present experiments as follows:

(i) A variety of exploration dynamics is evident. Even for a fixed figure on the plane, an agent switches from one navigation style to the other patterns spontaneously. The switching behaviour from one navigation style to the others is well correlated with the switching of the internal neural activity.

(ii) The scanning speed of the sensors and the spatial scale of the texture pattern determine the internal states of the neural dynamics. Spatial scales are translated into time scales of the internal stimuli. As a result, the internal network tunes its navigation style on the plane, which in turn determines the succeeding input patterns. In particular, the instability source is introduced by a combination of the spatial scale, the navigation time scale, the time scale of internal signal transfer and the signaling time scale. In order to prevent numerical error, we don't look into a fast scale event shorter than the pulse-train width. Also, the proportion between the navigation scale and the signaling time scale is an essential controlling factor. Here we have dealt with them as having equal time scales, but we need to determine the factor through an evolutionary selection or some other examinations. The studies on the evolutionary process of these scales will be reported elsewhere.

(iii) We have observed that neural states in a local periodic attractor are robust against the environmental inputs. On the other hand, the chaotic transients are ready for receiving the inputs. This may be caused by the fact that periodic attractors generate localized patterns but chaotic ones have more distributed ones. This difference of the navigation pattern is directly reflected in the input time series. The above observations suggest that an agent doesn't simply respond to the physical stimuli, but is responding to the 'time structure of the input stimuli'. That is, *the way an agent perceives the world is based, not on a snapshot of "sense-data", but on the temporal flow of the 'sense-data'.*

6. Discussion

Embodied Chaotic Itinerancy is an inevitable outcome of coupled unstable neural dynamics. The outcome of such unstable dynamics is the attachment-detachment switching described here. When an agent is attached to the environment, it intends to process the sensory data flow. When it is detached, it obeys its internal dynamics. We claim that conscious states emerge when a subject spontaneously selects one of the two phases. This is what we have described as 'autonomous coupling' (Iizuka and Ikegami, 2004), where an agent autonomously connects to,

and disconnects from the sense-data. With the evolved neural weights and chaos dynamics, the agent obtains two different action organizations against different light patterns. We propose such autonomous attaching-detaching behaviour as an indication of a protoconscious state, following the ideas of Henri Bergson and J.J. Gibson.

Henri Bergson's notion of mental imagery (1911) can be seen in the interplay between motion and internal chaotic dynamics. His idea was to consider perception as a process based on the motion structure. Gibson (1962) implicitly inherited the idea and proposed a theory of active perception. The active perception approach considers that perception isn't caused by momentary sense data but by the successive stimuli of sensation. Exploration isn't executed inside of a memory space but in the real space. It is automatically guided by consecutive sensory flow from the outside. Muenzinger (1938) and Tolman's (1948) vicarious trial-and-error experiments, or the more recent microchoice experiments of Brown (1992) show that normal rats demonstrate 'private' simulation or pantomime-like behaviours in some maze solving tasks. Recently, there have been interesting electro-physiological studies on Drosophila from Swinderen, Nitz and Greenspan (2004) on voluntary/involuntary activities. The data showed that flies do sleep and can probably even dream as their limb motion can be temporally decoupled from their nerve systems.

These findings, together with our simulation experiments, lead us to think that living systems have developed a dynamic interface between the inside and outside of the system. Varela argued for biological cognition and autonomy by proposing a new theory called autopoiesis (Varela, Maturana and Uribe, 1974; Varela, 1979). The surplus of signification of an autopoietic system provides the origin for cognition. To construct the world requires identity, which amounts to self-produced coherency as a unity. In an example of a cellular autopoietic system, self-produced coherency is generated from interactions between a catalyst and other particles. An emergent boundary which separates outside and inside, regulates the complex internal interaction as a single unit. The boundary is maintained dynamically by the internal network. This circulation provides 'autonomy' with self-produced coherence as a unit (e.g. Varela et al. 1974; Suzuki and Ikegami, 2004; forthcoming).

We suggest that our mobile agent here shares the same concept of boundaries with autopoietic systems. The present simulation implies that the sensors and styles of motion form a circular relationship like autopoiesis. The time structure of the sense-data, not a momentary sensory pattern, organizes the perceptual landscape, which co-ordinates

the internal neural dynamics and the time structure itself is generated by the self-motion pattern. This circular relation between sense- data and styles of motion organize what we call active perception. Perception of objects is thus inevitably grounded on styles of motion, which is named 'affordance' in ecological psychology (Reed, 1996).

We have observed that in some chaotic-itinerant dynamics, local chaotic transient states are ready for taking input signals and local periodic ones reject inputs. Perception doesn't require attachment between an agent and an object all the time, but the temporal detachment is a natural phenomenon when an agent is autonomous. An agent can perceive the world by mixing alternatively with the sensory flow from the surroundings and the internal neural dynamics. (For example, we have demonstrated the advantage of this concept in designing a small agent with a Hebbian neural net and letting her evolve to discriminate rectangles from triangles by tracing/skimming object forms (Morimoto and Ikegami, 2004). Our contention is that sensors can only process sense data when a conscious state exists behind the physical sensors. But processing sense-data again needs to be clarified. As the first step towards implementing a machine consciousness, we define the conscious state as a form of exploration of possible motion styles embedded in neural attractors. Spontaneous attachment-detachment from the environment is an outcome of this internal exploration, which may be corresponding to vicarious trial-and-error or microchoices. In other words, sensors with a conscious state imply that any perception is essentially an active perception because an agent perceives the world as the temporal flow of the 'sense-data' which is generated by its own embodied motion. Chaotic itinerancy must be embodied, (i.e. ECI), which is essential for the active perception.

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Appendix

An FHN neuron consists of two variables, a 'fast' variable (u), responsible for the excitation of a membrane potential, and a 'slow' variable (v), responsible for its non-responding (refractory) dynamics. Here the input signal I(t) is posed on the fast variable u.

$$\frac{du}{dt} = c(u - \frac{u^3}{3} - v + I(t)) \qquad (A1)$$

$$\frac{du}{dt} = a + u - bv \qquad (A2)$$

The output neurons cooperatively constitute the motor actions. When an output neuron m is activated, it produces a rectangular pulse of a length h. Here the typical value is 1.5. Motion of the agent is controlled by the two forward forces, where each force is computed from two output neurons, respectively.

$$F_L = \tanh(h_1^L(t) + h_2^L)) \qquad (A3)$$

$$F_R = \tanh(h_1^R(t) + h_2^R)) \qquad (A4)$$

The equation of the agent navigation motion is described by the pair of equations with two variables; a heading direction θ and a space displacement vector (x,y) as follows. The typical coefficient values are g1=15 and g2=50.

$$(\frac{dx}{dt}, \frac{dy}{dt}) = g_2 (F_L + F_R)(\cos(\theta t), \sin(\theta t)) \qquad (A5)$$

$$\frac{d\theta}{dt} = g_1(F_L - F_R) \qquad (A6)$$